Water Research 260 (2024) 121946

Contents lists available at ScienceDirect

Water Research

journal homepage: www.elsevier.com/locate/watres

Effects of landscape changes on water quality: A global meta-analysis

Xinying Shi [a], Dehua Mao [a,*], Kaishan Song [a], Hengxing Xiang [a], Sijia Li [a], Zongming Wang [a,b]

[a] State Key Laboratory of Black Soils Conservation and Utilization, Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences, Changchun 130102, China

[b] National Earth System Science Data Center, Beijing 100101, China

ARTICLE INFO

Keywords:
Landscape changes
Water quality
Meta-analysis
Water security
Global scale

ABSTRACT

Landscape changes resulting from anthropogenic activities and climate changes severely impact surface water quality. A global perspective on understanding their relationship is a prerequisite for pursuing equity in water security and sustainable development. A sequent meta-analysis synthesizing 625 regional studies from 63 countries worldwide was conducted to analyze the impacts on water quality from changing landscape compositions in the catchment and explore the moderating factors and temporal evolution. Results exhibit that total nitrogen (TN), total phosphorus (TP), and chemical oxygen demand (COD) in water are mostly concerned and highly responsive to landscape changes. Expansion of urban lands fundamentally degraded worldwide water quality over the past 20 years, of which the arid areas tended to suffer more harsh deterioration. Increasing forest cover, particularly low-latitude forests, significantly decreased the risk of water pollution, especially biological and heavy metal contamination, suggesting the importance of forest restoration in global urbanization. The effect size of agricultural land changes on water quality was spatially scale-dependent, decreasing and then increasing with the buffer radius expanding. Wetland coverage positively correlated with organic matter in water typified by COD, and the correlation coefficient peaked in the boreal areas (r=0.82, $p < 0.01$). Overall, the global impacts of landscape changes on water quality have been intensifying since the 1990s. Nevertheless, knowledge gaps still exist in developing areas, especially in Africa and South America, where the water quality is sensitive to landscape changes and is expected to experience dramatic shifts in foreseeable future development. Our study revealed the worldwide consistency and heterogeneity between regions, thus serving as a research roadmap to address the quality-induced global water scarcity under landscape changes and to direct the management of land and water.

1. Introduction

The global landscape has undergone profound changes in recent decades due to the accelerating development of human societies, coupled with climate changes that, in turn, drive further alternations in climate and disturb the provision of ecosystem services (Pielke Sr, 2005; Song et al., 2018; Olsson et al., 2019). Human-induced landscape changes, especially brought about by agricultural production and urbanization, have affected nearly three-quarters of the global terrestrial area and the transformations continuously intensified (Winkler et al., 2021; Zalles et al., 2021). Nevertheless, natural landscapes, particularly forests and wetlands, have faced pervasive loss over the past centuries (Mao et al., 2018a; Mao et al., 2018b; Fluet-Chouinard, 2023). Although land degradation has received concordant perception from international governments (Olsson et al., 2019), global landscape changes manifest substantial aggravation and unevenness resulting from regional divergence in geographic and socioeconomic conditions (Sun et al., 2020; Radwan et al., 2021). Continuous landscape changes have now surpassed climate change as the primary factor influencing ecological processes in watersheds (Dale, 1997; Delpla & Rodriguez, 2014), significantly affecting regional water quality by impacting the biogeochemical and hydrological cycles, posing challenges to interregional environmental equity and worldwide water security (Bullard et al., 1966; Peiffer et al., 2021).

Water security has been at the center of the world's attention as a necessity for supporting lives and the well-being of humans (Vörösmarty et al., 2010). However, the handily available freshwater in ecosystems encompassing rivers, lakes, and wetlands constitutes a fraction of less than 1 % of the total water volume and faces continuous endangerment (USGS, 2019). Saving the water quality is critical for alleviating water

* Corresponding author.
E-mail address: maodehua@iga.ac.cn (D. Mao).

https://doi.org/10.1016/j.watres.2024.121946
Received 21 February 2024; Received in revised form 12 June 2024; Accepted 13 June 2024
Available online 14 June 2024

scarcity, salvaging Sustainable Development Goals, and also supporting food and energy security (Wang et al., 2022a). Landscape changes have emerged as a major contributor to the deterioration of water quality in the Anthropocene, marked by the reinforced contamination inputs from land use activities and a weakened capacity of the natural landscape for decontamination (Bullard, 1966; IFPRI & VEOLIA, 2015). Examples include excess nutrients such as nitrogen and phosphorus in water bodies caused by agricultural inputs, and elevated bacteria concentrations discharged from urban sewage (Carpenter et al., 1998; Kang et al., 2010). At the same time, the conversion from natural landscapes to anthropogenic land covers leads to soil erosion, transporting sediments and organic carbon into receiving water and reducing pollutant purification capacity (Sweeney et al., 2004; Tan et al., 2022). However, whether the impacts of worldwide uneven landscape changes on water quality are consistent and whether they have become stronger in recent years remains unknown.

Copious regional-scaled studies have been conducted on the effects of landscape changes on water quality with a wide spectrum of methods, indicating that landscape patterns broadly contribute to the formation, release, interception and decomposition of pollutants in water (Bullard, 1966; Simpson et al., 2022; Tan et al., 2022). In the majority of these studies, changes in the landscape were focused on land use/land cover (LULC) shifts (Mehaffey et al., 2005; Flood et al., 2022). The data source of landscape changes experienced an evolution from rough field surveys or historical planning documents (Hakamata et al., 1992; Broussard, 2009), to broadscale, dynamic and high-resolution remote sensing imageries in recent years (Rimba et al., 2021; Zhang et al., 2022). The surface water quality could be revealed by levels of various indicators like pH, electric conductivity, concentrations of solids, nutrients, bacteria, heavy metals, etc. (Lee et al., 2009; Chiang et al., 2021; Flood et al., 2022) or composite water quality indices (WQI) (Zhang et al., 2022). Commonly used quantitative methods to examine the response of water quality to landscape changes were correlation analysis (Chiang et al., 2021), principal components analysis (Galbraith & Burns, 2007), redundancy analysis (Sliva & Williams, 2001), and linear regression analysis (Mehaffey et al., 2005). As machine learning algorithms developed, some studies have employed them concerning complex environmental variables, represented by the random forest model (Zhang et al., 2022; Xu et al., 2023) and the support vector machine model (Luo et al., 2020).

However, there is still a gap in research globally addressing the consistency and heterogeneity among numerous studies with divergent answers on how landscape changes affect surface water quality, since complex environmental factors moderate the results. Firstly, previous studies were conducted at small scales, and worldwide analyses have been restricted to specific landscape types or water body types. Brauns et al. (2022) synthesized 125 studies to reveal the human impacts on fresh water in streams and rivers. Qiu et al. (2023) compiled 66 studies from around the globe on the impacts of forest cover changes on water quality. Yet, so far, the responses of water quality indicators to various landscapes at the global scale, especially the fast-degrading wetlands, are still unclear. Secondly, previous literature at regional scales has not reached a global consensus due to the strong heterogeneity in natural environment and socio-economic conditions worldwide. For example, some studies concluded that agricultural development was largely responsible for increasing the total phosphorus (TP) in water (Vaighan et al., 2017; Wei et al., 2020), while some other studies claimed TP concentration had the strongest correlation with urban sprawl (Ren et al., 2003; Chiang et al., 2021). Additionally, some of the study results could even be counterintuitive. For instance, forests might contribute to the total suspended solid (TSS) output to water (Quinn & Stroud, 2002; Tromboni et al., 2021), and wetland coverage could be positively related to total nitrogen (TN) and TP concentrations (Giri et al., 2018). Therefore, there is a necessity for a review that provides robust quantitative syntheses across prodigious studies worldwide to comprehend the effects of landscape changes on water quality and the variation pattern in the global context.

In this paper, a global meta-analysis is performed to address the following questions: (1) What are the study trends and hotspots of the effects of landscape change on surface water quality until now? (2) What are the overall correlations between kinds of landscape changes and water quality? (3) What are the moderators in their correlations? And how do the correlations vary under different moderators? This paper initially identifies the worldwide consistency and heterogeneity between regions regarding the relationship between landscape changes and surface water quality, underpinning global knowledge and equity in water security.

2. Materials and methods

2.1. Data collection and compilation

To collect data for analysis, over 20,000 peer-reviewed publications were queried until December 2022 through Web of Science, ScienceDirect and China National Knowledge Infrastructure Databases. Duplicates and inaccessible articles were removed by machine screening, while irrelevant articles were removed from the preliminary scanning of titles and abstracts. Later the 625 selected studies were full-text scanned and compiled with their characteristic information (Fig. 1). A Detailed flow diagram is shown in Appendix 1. Landscape compositions of interest were agricultural lands (AG), urban lands (UR), forests (FO), grasslands (GR), wetlands (WET), water bodies and barren lands. Herein, landscape changes refer to the change in proportion of each composition in a certain watershed. Concerned water quality parameters included acidity (pH), electrical conductivity (EC), dissolved oxygen (DO), total suspended solids (TSS), total dissolved solids (TDS), total nitrogen (TN), nitrate, ammonia, total phosphorus (TP), phosphate, chemical oxygen demand (COD), total biological oxygen demand (BOD), dissolved organic carbon (DOC), coliform, metal ions (K, Ca, Na, Mg, etc.) and heavy metals (Cu, Zn, Mn, Pb, etc.).

From each of the studies, we extracted the correlation coefficients of landscape composition changes versus water quality indicators as effect sizes in the meta-analysis, which emphasized the interactions between variations (Borenstein et al., 2009), since the absolute changes of water quality parameters have tremendous discrepancy worldwide due to the inherent geographical differences in the global water environments. A set of 3228 data from 179 studies was finally extracted according to the following criteria for studies: (i) reporting at least one correlation metric that could be transformed into Pearson Correlation Coefficient (r); (ii) only *in-situ* research, excluding data calculated by model simulation; (iii) research implemented in different catchments reported in one article should be considered as independent studies; (iv) water quality data should either be obtained through parallel sampling and measured following specifications, or from authorities, both should record sampling locations; (v) study objects should be surface water in common conditions without forcing factors (e.g. mining, fire, etc.).

To normalize the correlation metrics in the dataset, we took the widely used Pearson Correlation Coefficient (r) as standard, commonly expressed as (Rupinski and Dunlap, 1996):

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})}} \quad (1)$$

Where X_i and Y_i are values of the i th independent variable and dependent variable, and $\overline{X}$ and $\overline{Y}$ are sample means. r takes the value from -1 to 1. The larger the absolute value, the stronger the correlation.

Spearman's Rho (ρ) and Kendall's tau (τ) correlation coefficients were converted to Pearson's r through the formula (2) and (3) (Rupinski and Dunlap, 1996).

$$r = 2\sin\left(\rho \times \frac{\pi}{6}\right) \quad (2)$$

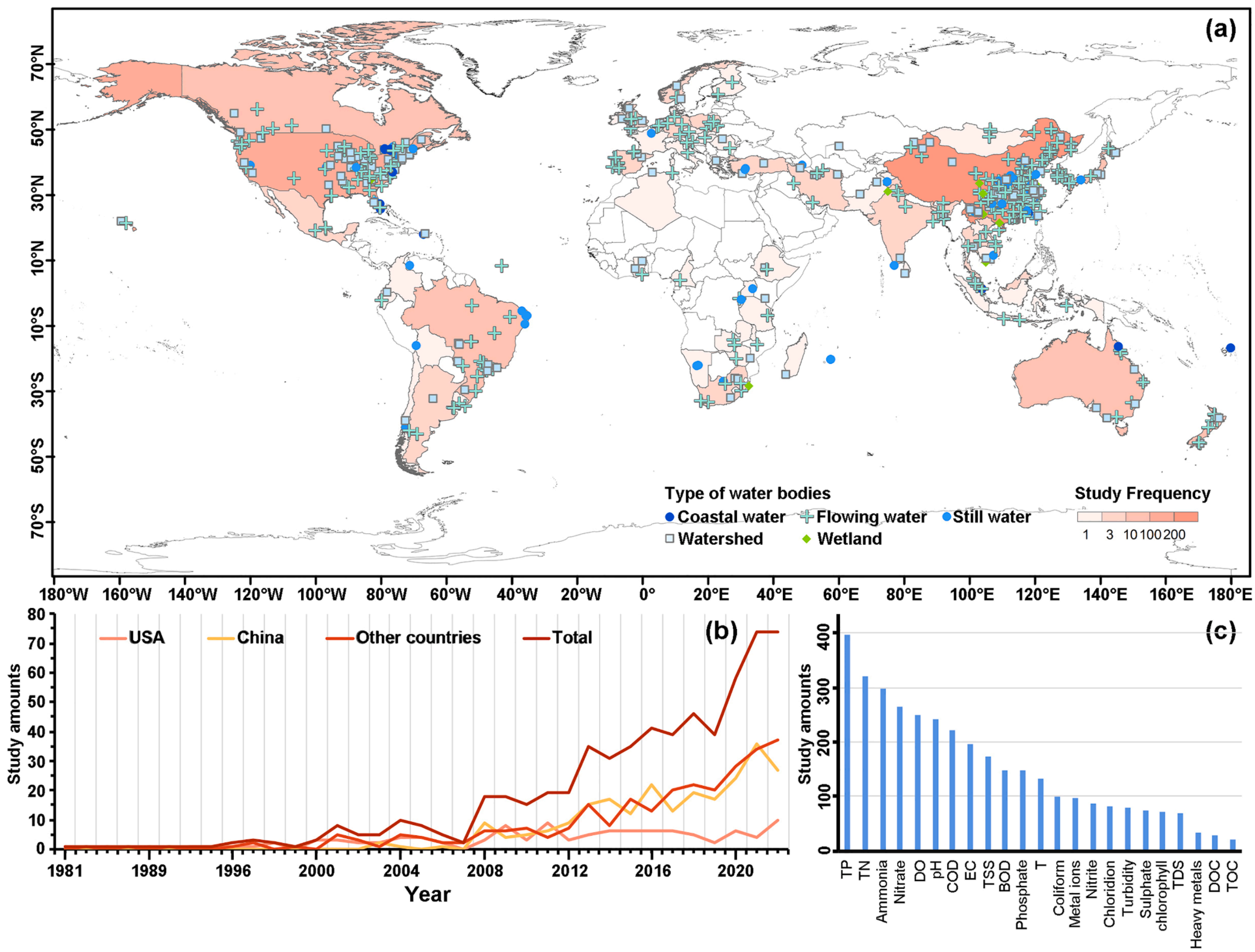

Fig. 1. (a) Geographic distribution of the 625 *in-situ* studies worldwide included in our meta-analysis. The darker the red in the background map, the more frequently the country is studied. All the study sites are grouped into five types according to the type of water body investigated, namely, coastal water, including coasts and bays; flowing water, including rivers and streams; static water, including lakes, reservoirs and small ponds; watershed by geographical boundaries; and wetlands. The amounts of studies on each of them are shown in the lower left corner. (b) Annual trends in the published papers studying the effects of landscape pattern changes on water quality. In addition to the overall trend in dark red, the trends of the USA and China, which account for the larger share of publications, are also shown separately from other countries. (c) Accounting for the study frequency of each water quality indicator.

$$r = \sin(0.5\ \pi\ \tau) \tag{3}$$

The coefficient of determination (R^2) of univariate linear regression was equivalent to the square of r and the sign of r was the same as that of the regression coefficient (Zou et al., 2003). In studies conducting redundancy analysis (RDA) with type II scaling, the cosine of the angle between the response variable and the explanatory variable was calculated to represent r (Legendre and Legendre, 2012). Data exhibited in the figures were extracted using GetData Graph Digitizer 2.25 (GetData Graph Digitizer, 2013).

To reveal the potential influencing factors for the worldwide variation in the effects of landscape changes on water quality, environmental information of those extracted studies was compiled, including the coordinates, types of water bodies, climate zones, seasons, spatial scales, and year. The majority of them were directly gleaned from the primary studies, except for the climate zones, which were allocated by coordinates in the Köppen-Geiger climate classification (Beck et al., 2018).

2.2. Data Analysis

Meta-analysis accompanied by statistical and machine learning methods was employed in this paper. Meta-analysis parts were implemented through the Meta Package in R studio (Schwarzer, 2007). Primarily, the r was converted to Fisher's z-transformed coefficients (Z_r), which could gain better normality in distribution and calculate reliable confidence intervals (Borenstein, 2009; Asuero et al., 2006), through the following formula:

$$Z_r = 0.5\ln\left(\frac{1+r}{1-r}\right) \tag{4}$$

And accordingly, sampling variance was also derived from (Fox et al., 2015):

$$\hat{\sigma}^2_{Z_r} = \frac{1}{n-3} \tag{5}$$

Where n is the sample size for r. Given that landscapes and water quality in global settings generally differed, Z_r within individual studies was then accumulated by inverse variance regression and random-effects model, which was more appropriate for cases with heterogeneity among studies than the fixed effect model (Borenstein et al., 2010). Eq. (6) and (7) provided a general statement of the random-effects model:

$$y_i = \beta_0 + \varepsilon_i + \xi_i \tag{6}$$

$$Y = \sum_{i=0}^{n} y_i \cdot w_i \tag{7}$$

Where y_i was the effect size of the i th study; ε_i represented deviation within study; whereas ξ_i represented deviation between studies, which obeyed the normal distribution with 0 as the mean and τ^2 as the variance. We performed the restricted maximum-likelihood method (REML) to estimate τ^2 and the Q-Profile method to calculate the confidence interval. Furthermore, Y in Eq. (6) was the accumulated overall effect size, while w_i representing the weight in the random-effects model was calculated from the inverse of the total variance with τ^2 as part of the denominator. I^2 was the proportion of between-study variance (τ^2) in total model variance, and in essence, indicated the heterogeneity in the overall effect after pooling (Borenstein et al., 2010). I^2 less than 40 % indicates negligible heterogeneity within the group of studies, and over 90 % indicates considerable heterogeneity (Deeks et al., 2022).

Above that, it was crucial to recognize the presence of publication bias (Nakagawa et al., 2017), which may lead to conclusions that deviate from the true results and therefore affect the validation. Hence, we generated symmetrical funnel plots and adapted Egger's test to examine the risk of bias (Nakagawa et al., 2017) (Appendix 2).

To further investigate the moderators affecting the effects of landscape changes on water quality, we separately established random-effect models within subgroups for categorical variables (e.g., water body types, climate zones, etc.) and adopted nonparametric statistical methods that greatly avoided affection by outliers and therefore reduced bias (Nahm, 2016). The Kruskal-Wallis test was used to inspect the overall heterogeneity among subgroups under each moderator and the Wilcoxon test suitable for non-independent samples was employed to further examine heterogeneity between two-by-two subgroups since some samples in different subgroups were from the same site. For the continuous variables (i.e., latitude and year), we combined the polynomial regression and random-effects meta-regression (a weighted regression model through REML), both for demonstrating variations in effect sizes under moderators.

The random forest model (RF) as a machine learning method was adopted to find the relative importance of moderators in impacting the response of water quality to landscape changes via the randomForest Package in R studio (Liaw and Wiener, 2002). Random forest regression allowed the explanation of influences and relative importance of multiple independent variables on the dependent variable, as an ensemble classifier encompassing multitudinous decision trees (Breiman, 2001), superior by reducing overfitting and the risk of synergy effect of interdependent variables (Merghadi et al., 2020), herein the moderators. Random forests had their variable importance calculated using two methods, of which the per cent Increase in Mean Squared Error (% IncMSE) was considered more robust, widely applied and thus employed here (Grömping, 2009; Feng et al., 2022). A higher %IncMSE implied stronger importance of that moderator.

3. Results

3.1. Overview of landscape-water quality studies

Based on the data compiled from 625 studies in 63 countries worldwide from 1976 to 2022 (Fig. 1a&b), we could be informed that major studies concentrated from latitude 30°N to 60°N, mainly in the Yellow River Basin and the Yangtze River Basin, China, the Mississippi River Basin and the Great Lake Region, USA and various basins in Europe (Fig. 1a). Studies on the relationship between landscape changes and water quality were almost in Northern America and the Europe before 2007. The years 2008 and 2020 witnessed rapid growth in study quantities, especially in China (Fig. 1b). To date, there have been large gaps in research in Africa and Northern Asia.

Around half of the studies investigated flowing water bodies like rivers and streams (Fig. 1a). One-third studied the watersheds (herein defined as a geographical area including all the water bodies rather than a specific type), then 10 % concerned the static water bodies like lakes and reservoirs. As for the water quality indicators influenced by land changes (Fig. 1c), nutrients (e.g., TP, TN and ammonia) gained major attention, measured in 2/3 studies, followed by physiochemical parameters (e.g., DO and pH). Organic pollutants revealed by COD and BOD were studied in nearly half of the references.

3.2. Overall effects of landscape changes on water quality

In the global context, five of the seven categories of landscape compositions exhibited significant impacts on water quality indicators when their coverage changed, namely urban lands, agricultural lands, forests, wetlands, and grasslands (Fig. 2a~e, Appendix 3). The shifts in urban land and forest coverage significantly correlated with water quality ($p<0.05$) and showed opposite effects with each other (Fig. 2a&b). There were appreciably positive relationships between urban land coverage and contaminations, including TSS (r=0.69, $p<0.01$), COD (r=0.66, $p<0.01$), Coliform (r=0.68, $p<0.01$) and Metal ions (r=0.65, $p<0.01$) (Fig. 2a). Increased urban land use would also significantly reduce DO (r= -0.56, $p<0.01$). In contrast, increasing forest coverage had significantly negative correlations with those pollution indicators in water ($p<0.05$) and improved the DO level (r=0.50, $p<0.01$) (Fig. 2b). Nevertheless, the aggravating effects of urban lands on contaminants were more profound than the purification effects of forests regarding TSS (r_{UR}=0.69, r_{FO}= -0.54), TN (r_{UR}=0.58, r_{FO}= -0.44), TP (r_{UR}=0.57, r_{FO}= -0.53), Heavy metals (r_{UR}=0.53, r_{FO}= -0.50) and Coliforms (r_{UR}=0.68, r_{FO}= -0.26) ($p<0.01$).

Expanding agricultural lands positively correlated with EC, Nitrate, TP, and DOC levels in water environment ($p<0.01$) (Fig. 2c). In comparison, the effects of agricultural land on water quality were not as substantial as that of urban land (Fig. 2a&c), for instance, on levels of TSS (r_{UR}=0.69, r_{AG}=0.51), COD (r_{UR}=0.66, r_{AG}=0.38), TN (r_{UR}=0.58, r_{AG}=0.44) and TP (r_{UR}=0.57, r_{AG}=0.49) ($p<0.01$).

Wetland occupancy demonstrated a robust correlation with EC decreasing (r= -0.87, $p<0.01$) and organic matter increasing ($p<0.01$), indicated by COD(r=0.57) and DOC(r=0.56) (Fig. 2d). However, the overall correlation between wetland cover with nutrient concentrations did not reach statistical significance at the global scale. The effects of grassland coverage shift on water quality were more ambiguous worldwide (Fig. 2e), with a significant negative correlation with TN, TP and phosphate ($p<0.05$) and a positive correlation with microbial contamination (r=0.72, $p<0.01$). The overall effects of landscape configuration on water quality, such as the patch density changes, were also enquired and attached in Appendix 4.

3.3. Moderators influencing the landscape - water quality relationship

3.3.1. Influence of latitude and the type of water bodies

Polynomial regression curves showed that the effects of landscape changes on water quality exhibited regularity along the latitude at the global scale (Fig. 3 a~c). The positive correlations of agricultural land coverage with TN and TP were gradually enhanced with increasing distance from the equator ($p<0.01$) (Fig. 3a&b). Conversely, the effects of forest coverage on TN and COD significantly weakened from low to high latitudes ($p<0.01$) (Fig. 3a&c), despite the restricted sample numbers in the southern hemisphere. Regarding the urban land coverage, its aggravating contribution to TP and COD levels perceptibly declined as the latitude rose ($p<0.05$ and $p<0.01$, respectively) (Fig. 3b&c). The effects of wetland coverage on TN, TP and COD levels were not significantly associated with latitude (p>0.05) (Fig. 3a~c).

Significant variations across different water body types were witnessed in the correlations between landscape changes and water quality (Fig. 3d~e). Among all the landscape compositions, the influence of agricultural land changes on water quality exhibited the most significant

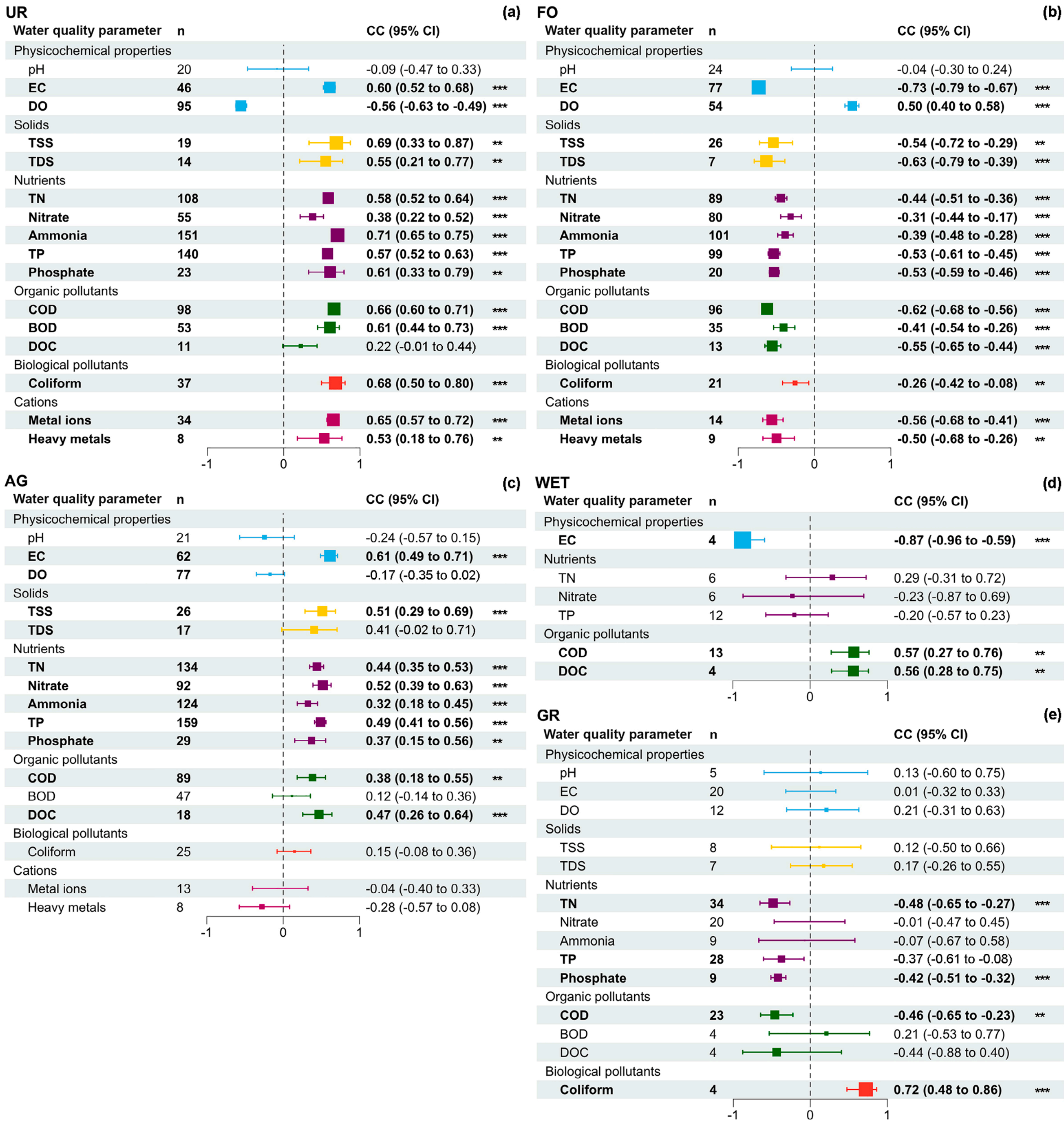

Fig. 2. Overall effects of Individual landscape composition on each water quality indicator under the random effects model. UR= Urban lands, AG = Agricultural lands, FO = Forests, WET= Wetlands, GR =Grasslands. Different colors for distinguishing water quality parameters: blue for physiochemical parameters, yellow for solids, purple for nutrients, green for organic pollutants, orange for biological pollutants, and magenta for metal cations. Bold font represents statistically significant correlations at $p < 0.05$. 'n' denotes the number of sampling data. Squares with error bars denote the overall correlation coefficients (CC) (r) and the 95 % confidence interval (CI). The greater the CC is above 0 indicates the stronger the positive relation is, and vice versa. The size of the square symbolizes the effect size. Note: '*' denotes $p < 0.05$, '**' denotes $p < 0.01$, '***' denotes $p < 0.001$.

heterogeneity in different water body types ($p < 0.05$) (Fig. 3d~e), of which the weakest influence was always exerted on water in watersheds rather than a specific type (Fig. 3d~e). Remarkably, the elevating effects of agricultural land on TN (r_{steams}=0.64, r_{rivers}=0.54) and TP (r_{steams}=0.74, r_{rivers}=0.63) were stronger in streams than in rivers ($p < 0.05$) (Fig. 3d&e). As the coverage of urban lands or forests changed, their weakest influences on water quality were mainly observed in reservoirs ($p < 0.05$) (Fig. 3e&f). Forests exerted the most efficient purification effect on TP in coastal water (r_{coasts}= -0.68, p=0.02) (I^2=0). Urban expansion had the most profound impact on COD level in lake water (r_{lakes}= 0.87, $p < 0.01$). When wetlands were regarded as a type of water body, they showed unique within-group response consistency globally (mostly I^2=0) under landscape changes (Fig. 3d~f).

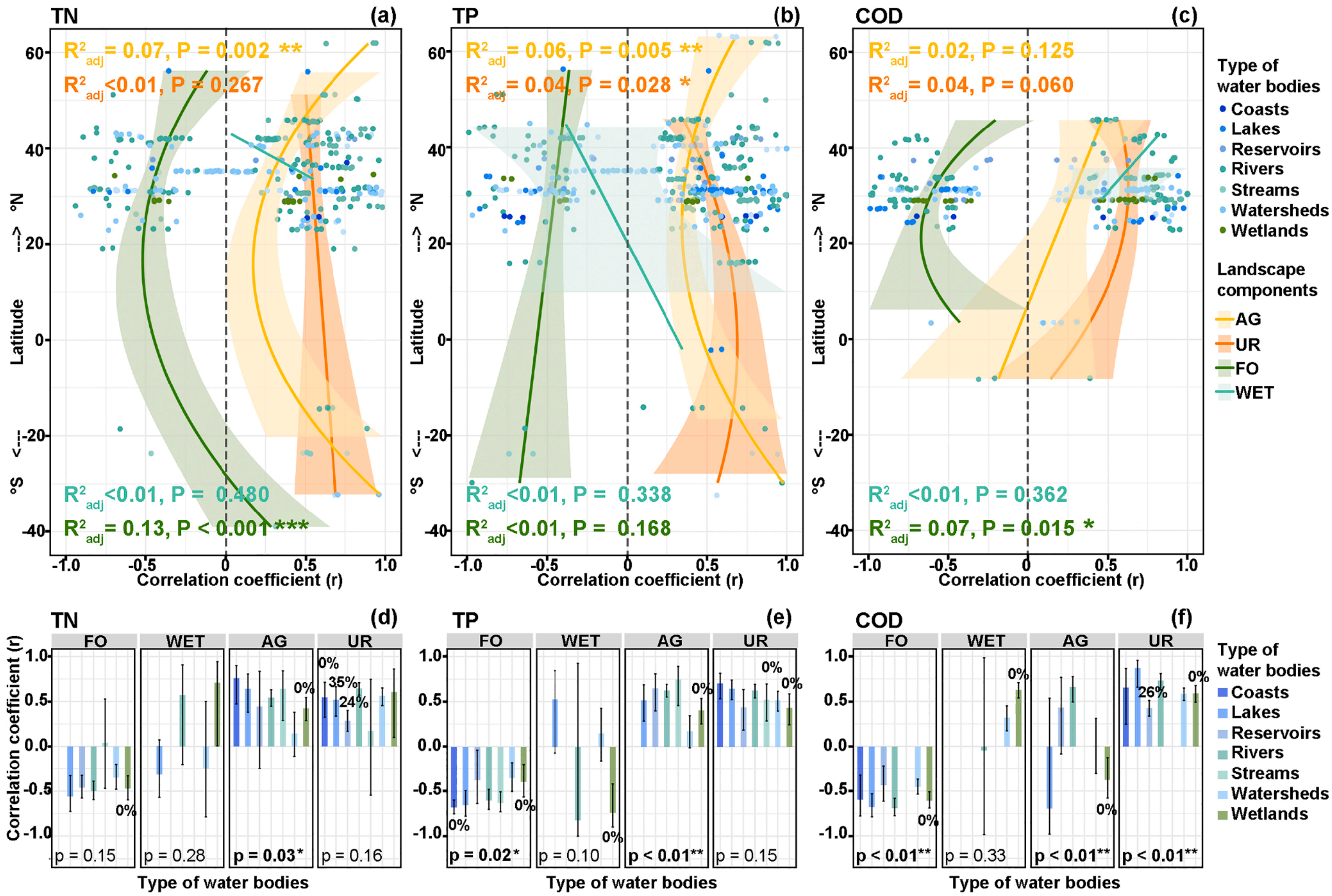

Fig. 3. Correlation coefficients between landscape compositions (AG, UR, FO and WET) and water quality parameters respectively TN (**a, d**), TP (**b, e**) and COD (**c, f**) moderated by latitude (**a~c**), and type of water bodies (**d~f**). (**a~c**) exhibit the polynomial regression curves for the correlation coefficient (r) with 95 % CI under latitude changes, the adjusted R^2 (R^2_{adj}) and significance (P) of which is also reported. (**d~f**) shows the correlation coefficient (r) within each water body type subgroup and the heterogeneity between subgroups by random-effect models, in which error bars denote the 95 % CI. Percentages adjacent to error bars are the I^2 value which is less than 40 % and indicates the heterogeneity within group could be ignored (Deeks et al.,2022). P-values for Kruskal- Wallis test are also reported beneath and those significant figures are bolded. Note: '*' denotes $p < 0.05$, '**' denotes $p < 0.01$, '***' denotes $p < 0.001$.

3.3.2. Difference between seasons and climate zones in effects of landscape on water quality

Climatic conditions could influence the temperature, precipitation, etc., thus making the relationship between landscape and water quality different among seasons and climate zones. Seasonally, the effects of landscape changes on TN and TP concentration were more powerful in the dry season and the rainy season than in normal period ($p < 0.01$) (Table 1, Fig. 4). The strongest effect size of forest on TN was r_{dry}= -0.73, on TP was r_{dry}=-0.70 and on COD was r_{dry}= -0.67 ($p < 0.01$), all appearing in the dry season. Similarly, the dry season witnessed the strongest boosting of agricultural land on TN (r_{dry}=0.65), TP (r_{dry}=0.72) and COD (r_{dry}=0.82) ($p < 0.01$). The influence of urban expansion on COD was rising as the season became moister, from r_{dry}=0.50 to r_{normal}= 0.62 to r_{wet}= 0.68 ($p < 0.001$). While the effects of wetland coverage change on water were not dependent on seasons (Table 1, Fig. 4).

Table 1
Kruskal-Wallis test *p*-value indicating the significance of the difference in the correlation coefficients contributed by the various moderators.

Moderators	TN	TP	COD
Seasonality			
WET	0.17	0.28	0.97
UR	**<0.01** **	**<0.01** **	**<0.01** **
FO	**<0.01** **	**<0.01** **	0.76
AG	**<0.01** **	**<0.01** **	0.16
Climate zone			
WET	0.64	0.28	**<0.01** **
UR	**<0.01** **	**<0.01** **	**<0.01** **
FO	0.73	0.12	0.23
AG	0.24	0.06	0.10
Spatial scale			
WET	0.38	0.59	0.80
UR	0.11	**0.01** *	0.12
FO	0.22	**0.03** *	1.00
AG	**<0.01** **	**<0.01** **	0.10

Note: '*' denotes $p < 0.05$, '**' denotes $p < 0.01$.

Climate zone could be a pronounced moderator under the urban land changes ($p < 0.01$) (Table 1). Expanding urban land coverage had the strongest impact on TN (r_{arid}=0.71), TP (r_{arid}=0.94) concentration and COD (r_{arid}=0.70) in the arid area among all the climate zones ($p < 0.05$) (Fig. 4). Although climatic zone was not as significant a moderator in the relationship between agricultural land changes and water quality as they were for urban land, the similar severity in arid areas also occurred with r_{arid}=0.78 for TN, r_{arid}=0.86 for TP and r_{arid}=0.83 for COD ($p < 0.01$). Besides, the elevating effects of wetlands on COD were significantly influenced by climate zones ($p < 0.01$) (Table 1), peaking in cold areas (r_{cold}=0.82, $p < 0.001$).

3.3.3. Spatial and temporal changes in the landscape - water quality relationship

The effects of landscape changes on water quality were scale-dependent both at spatial and temporal scales. When the geographic scale of investigation was adjusted, the effects of agricultural land on nutrient concentrations experienced the most apparent variation

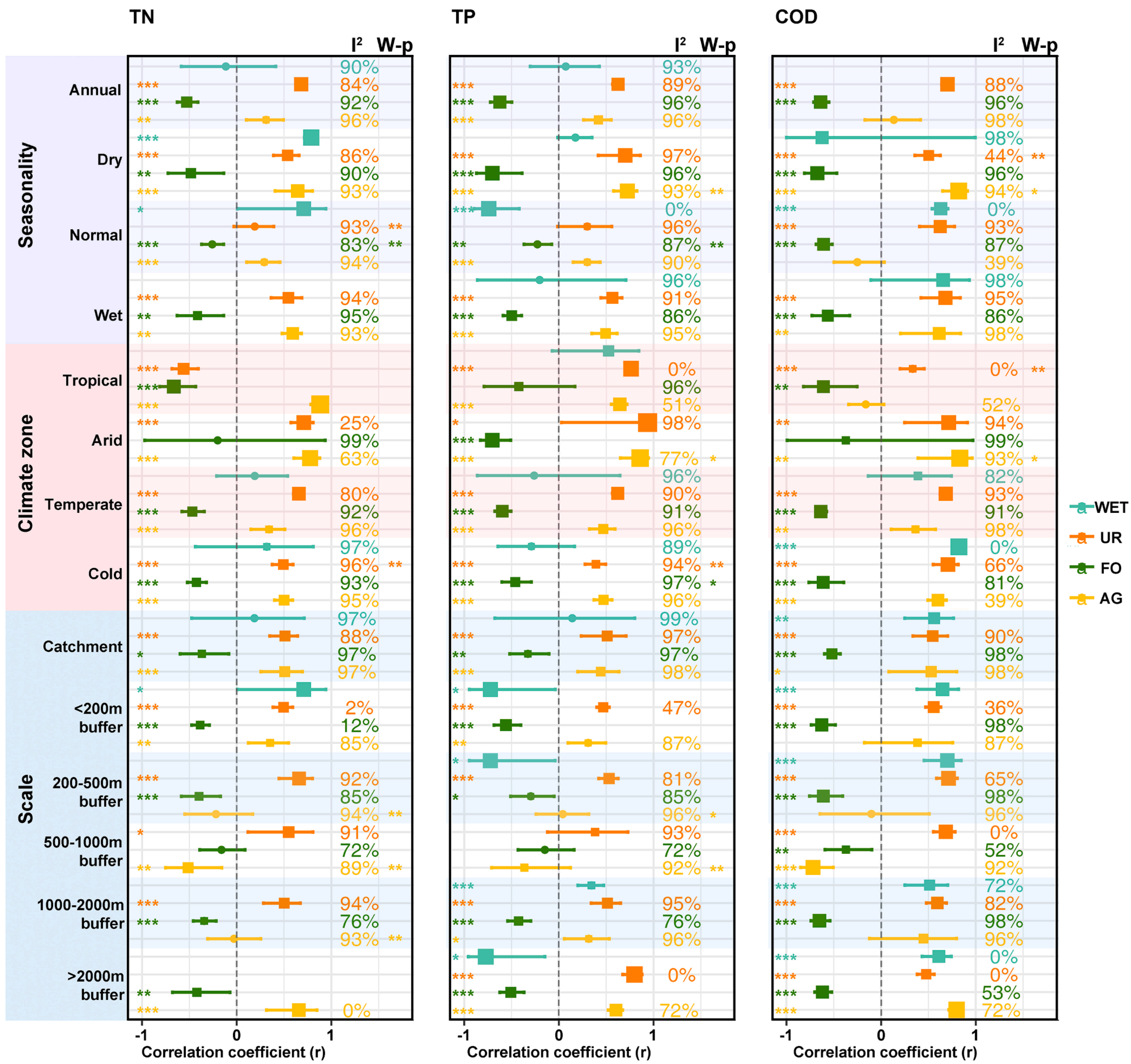

Fig. 4. Summary of correlation coefficients between landscape compositions (AG, UR, FO and WET) and water quality parameters respectively TN, TP and COD moderated by seasonality, climate zone and scale under the random effects model. '*' denotes $p < 0.05$, '**' denotes $p < 0.01$, '***' denotes $p < 0.001$. The square with error bar denotes the correlation coefficients (r) and 95 % CI for each subgroup. The greater the CC is above 0 indicates the stronger the positive relation is, and vice versa. The size of the square symbolizes the effect size. The I^2 value represents the heterogeneity within individual subgroups in the random effects model. Smaller I^2 implies less heterogeneity within the subgroup. The W-p significance is from the Wilcoxon test for the disparity between each subgroup and a certain subgroup of their moderator (i.e., Annual of the Seasonality, Temperate of the Climate zone, and Catchment of the Scale).

($p < 0.01$) (Table 1). There was a tendency in Fig. 4 that as the buffer radius expanded outwards along the water body boundaries, the correlation coefficients between agricultural land coverage and water quality parameters decreased until 500-1000m and then climbed to the maximum when the buffer was over 2000m (W-$p < 0.05$). Similarly, buffer scales significantly modulated the effects of forest and urban land on TP concentration ($p < 0.05$) (Table 1), in which a similar decreasing and then increasing tendency of effect size as the scale broadened also held. Further, the impacts of the above landscape changes on water environment at larger scales tended to witness a global consistency, i.e., at the catchment scale ($p < 0.05$) or the >2000m buffer scale ($p < 0.001$) (Fig. 4). In addition, responses of water quality to wetland coverage changes did not show significant differences across diverse spatial scales (Table 1).

From the perspective of temporal evolution, the meta-regression lines exhibited an intensifying tendency in the impacts of all four landscape composition changes on water quality from pre-1990 to 2022 (Fig. 5a~c). The correlations of agricultural land changes with TN and TP showed a concave trend through time, leading to a smaller effect size in the 2020s than in the 1990s ($p < 0.01$) (Fig. 5a&b). Studies on water quality response to land changes in urban areas and forests emerged around 1995, later than those in agricultural uses. The temporal variation of urban land and forest effects on water quality appeared synchronized, whether along the linear growth (for TN and TP) or fluctuating growth (for COD). In particular, all the growth rates of the effects of forest were higher than those of urban land ($p < 0.05$). Their

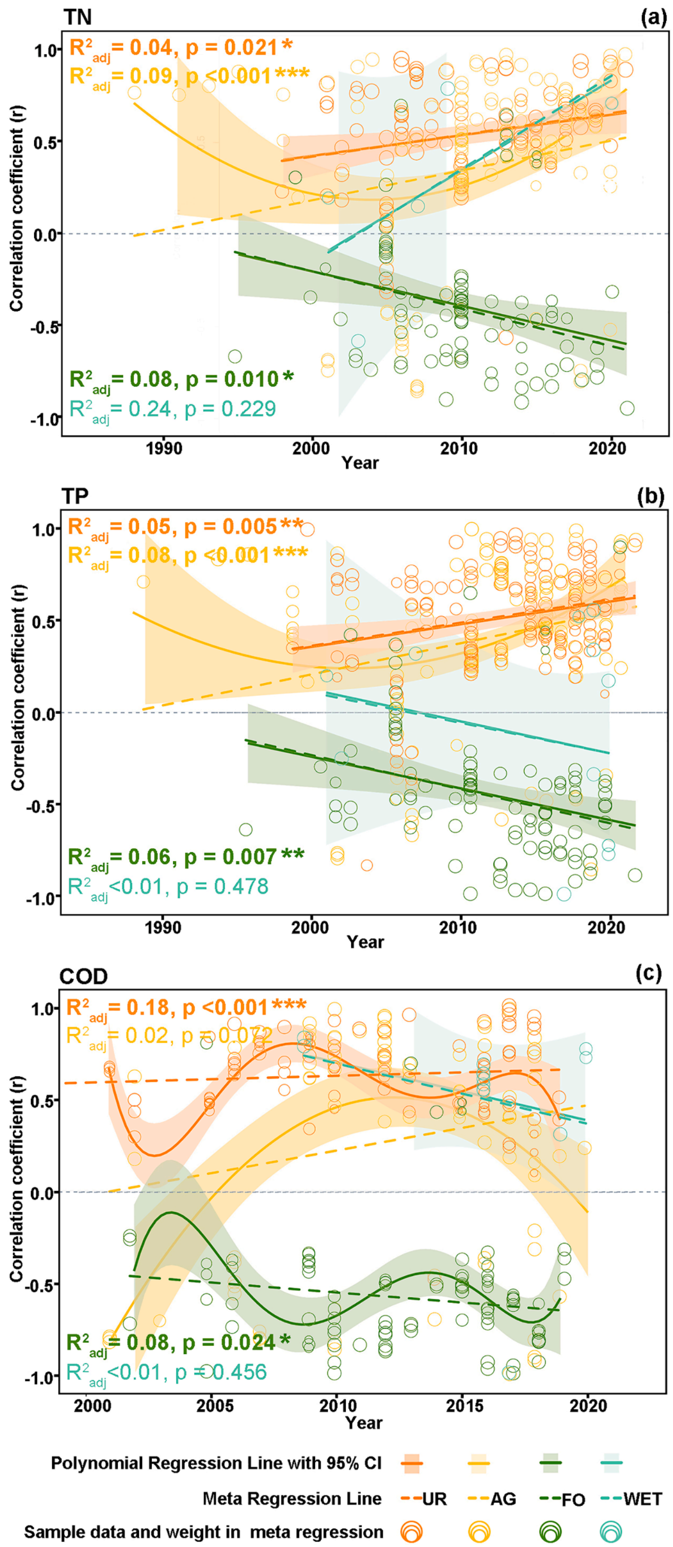

Fig. 5. Temporal changes of the correlation coefficients between landscape compositions (AG, UR, FO and WET) and water quality parameters respectively (**a**) TN, (**b**) TP and (**c**) COD. The solid line with 95 %CI denotes the relation curve fitted by polynomial regression, and the adjusted R^2 (R^2_{adj}) and significance (P) of which are also reported. The dotted line denotes the relation curve fitted by random-effects meta-regression with the circle representing sample data, whose size is proportional to the weight of effect size. Note: '*' denotes $p<0.05$, '**' denotes $p<0.01$, '***' denotes $p<0.001$.

coupled trends might result from their dominantly opposite effects (Fig. 2a&b), i.e., forests could perform the purification capacity to a greater extent as the pollution intensity of urban land rose when the pollutant concentrations were not saturated. As for wetland coverage changes worldwide, its effects on water quality were not significantly changed over time ($p>0.05$) (Fig. 5a~c).

3.4. Importance analyses of moderators to water quality variables

The random forest regression furnished the orders of the relative importance of moderating variables above (Fig. 6). Latitude most significantly influenced the correlation between agricultural land and water quality, in which scale and year were also among the critical moderators (Fig. 6a). It could be generally concluded that climatic conditions exerted less significant adjustments on how agricultural coverage changed water quality (Fig. 6a~c). Whereas seasonality had a prominent role in the response of water quality indicators to changes in riparian urban lands (Fig. 6d~f). Moreover, the rankings demonstrated that latitude was way ahead as an important explanatory factor for the variation of forest impacts on TN, TP and COD (Fig. 6g~i). Compared with the three landscape components above, the effects of wetland on water quality tended to be dependent on climate zone (Fig. 6h&i).

4. Discussion

4.1. Study trends and hotspots

Our global review revealed that the shifting of research centers of the landscape-induced water quality changes, as shown in Fig. 1a, was fully correlated with the regional socioeconomic development and urbanization process through time (Sun et al., 2020; Radwan et al., 2021). The quantitative research on the correlation between agricultural occupation and water quality started earlier than the other landscape types as shown in Fig. 5, echoing a series of policies such as the Clean Water Act in the USA in 1972 to control NonPoint Source pollution (NPS) (Haith, 1976; Mansaray et al., 2018). As demonstrated in Fig. 1, chemical, bacterial, and sediment loadings from NPS, mostly resulting from land runoff and hard to detect, had subsequently been a sustained academic concern and the USA dominated the studies (Wilkin and Jackson, 1984; Dauer et al., 2000; Mehaffey et al., 2005). The Pollution Prevention Act launched in the USA in 1990 and the Law of the People's Republic of China on the Prevention and Control of Water Pollution in 1996 might be part of the drivers of emerging studies on the effects of urban lands and forests on water quality around 1996 as shown in Fig. 5, matching the upward trend of study amounts. With the increasing worries about water quality changes under human activities and climate changes after 2000, the research on their dynamic relationship was universally enriched (Fig. 1), integrating methods such as the Better Assessment of Integrating Point and Non-point Sources (BASINS) framework (Bhattarai et al., 2008), ArcView Generalized Watershed Loading Function (AVGWLF) model (Tu, 2009), and other conceptual models for simulating future changes under different scenarios (Erol and Randhir, 2013). The emphasis in the Chinese Government's 11th Five-Year Plan (2006-2010) on mitigating climate change and strengthening projections for pollutant additions could have stimulated the exponential growth of China's research in 2008 (Xu et al., 2019), as illustrated in Fig. 1b. Attention to relevant issues globally spiked again around 2020, of which studies about the impacts of LULC changes on water quality reached new levels in developing countries in Africa and South America, for instance, Bolivia (Gossweiler et al., 2019), Cameroon (Ewane, 2020), Ethiopia (Woldeab et al, 2019), Ghana (Gyimah et al, 2020), Uruguay (Gorgoglione et al, 2020), and Zambia (Winton et al, 2021). Nonetheless, as revealed in our map (Fig. 1a), some places were still vacant without studies, even if facing the intensifying water quality challenges caused by landscape changes (Fig. 5).

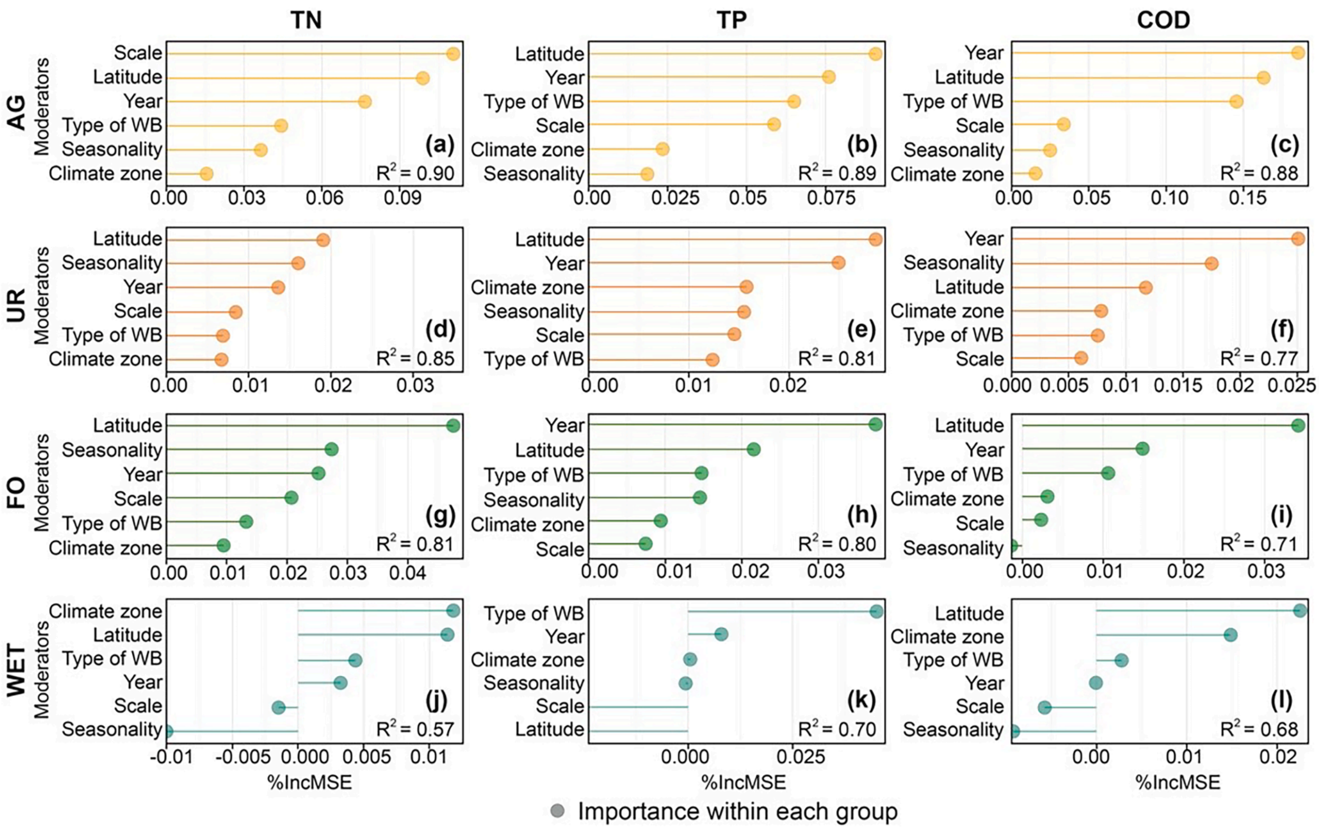

Fig. 6. Relative importance rank of various factors on variation in effects of changes in the landscape (AG, UR, FO and WET) on water quality, represented by the impacts on TN (**a,d,g,j**), TP (**b,e,h,k**), and COD (**c,f,i,l**). Importance decreases from top to bottom. The R^2 of random forest model is also reported separately in the figure. Fig. 6 Relative importance rank of various factors on variation in effects of changes in the landscape (AG, UR, FO and WET) on water quality, represented by the impacts on TN (**a,d,g,j**), TP (**b,e,h,k**), and COD (**c,f,i,l**). Importance decreases from top to bottom. The R^2 of random forest model is also reported separately in the figure.

4.2. Effects of agricultural lands on water quality

Our meta-analysis results substantiated that increasing agricultural land coverage in the catchment actively contributed to nutrient pollution and solids concentration in water worldwide (Fig. 2c). A considerable amount of nutrients that were not fully utilized in fertilizer and feed inputs in modern intensive farming and livestock farming entered the water with irrigation water and surface runoff, enriching N and P in the water and causing harmful eutrophication (Woli et al., 2004; Khan and Mohammad, 2014). Additionally, agricultural activities such as ploughing and irrigation undeniably caused water erosion and increased both suspended and dissolved solids in water (Chen et al., 2017). At the same time, the nutrients in particulate matter, especially phosphorus, would be further released into the aquatic environment (Horppila, 2019).

The spatial-scale effect was witnessed in the nonpoint-source pollution exported from agricultural land (Table 1, Fig. 6) since distance greatly affected the transport and transformation processes of the abovementioned pollutants (Sliva and Williams, 2001; Tu and Xia, 2008). Our global meta-analysis settled the long-term dispute and informed that the most powerful influencing scales of agricultural land for water quality were the whole catchment and over 2000m buffer scale since they had no statistical differences (Fig. 4). Before our study, the 200m buffer scale (Tran et al., 2010), 500m buffer scale (Gove et al., 2001) and catchment scale (Sliva and Williams, 2001; Zhang et al., 2019) were previously identified as the most significant scales in influencing water quality when landscape changed within watersheds. Further, our results indicated that study results worldwide held the largest consistency at the catchment scale compared with other buffer radiuses (Fig. 4).

Apart from the changes in effect size, we found that agricultural land could show opposite effects on water quality at different scales at the first time (Fig. 4), which universally presented a negative correlation within 500-1000m proximity riparian. A possible explanation was that other landscape compositions might cause compelling impacts that overpower the positive effect of agricultural land on water pollution. For instance, when urbanized spaces increased faster or in highly urbanized areas as in studies by Tu and Xia (2008) and Zhao et al. (2015), the existence of agricultural land might be obscured and presented a negative correlation with water quality deterioration. Another factor we could take into interpretation was the endogenous characteristics of the agricultural lands. It has been reported in several studies that paddy, instead of other cropland, might have a capacity for pollution reduction by strong plant absorption stimulated by appropriate environmental conditions in growth (Jung et al., 2008; Zhang et al., 2010). However, due to the substantial heterogeneity in geographical environment between watersheds, any future study on a single scale should be cautious and the threshold effects in the impacts of agricultural land coverage on water quality are expected for further investigation.

4.3. Response of water quality to urbanization

Our synthesized analysis proclaimed that contaminant increase and DO decrease in surface water caused by urban expansion have persisted worldwide for decades (Fig. 2a). Continuous impervious lands caused massive nonpoint-source pollution by surface runoff exporting solids, nutrients, and particularly, organic, bacterial, and heavy metal pollutants (Miller and Hutchins, 2017; Viau et al., 2011; Kang et al., 2010).

Concentrated pollution from urban lands could alter the processes of regional biogeochemical cycling and consume DO in water (Tong et al., 2020). Further, compared with agricultural landscapes, the urban environment could increase regional rainfall and thus boost the washing and leaching of contaminants from dust, food remnants and maintained greenspaces (Liu and Niyogi, 2019; Morée et al., 2013; Simpson et al., 2022). Considering that, our meta-analysis indicated that nutrients like TN and TP related more strongly to urban lands than agricultural productions (Fig. 2aandc).

Our study further demonstrated that the worldwide correlation variation of water quality with urban land coverage was dramatically related to climate conditions, especially seasons (Table 1, Fig. 6e~f). The overall impacts of urban lands on water quality in both wet and dry seasons were more severe than those in normal seasons with distinct mechanisms (Fig. 4). The wet season represented greater surface runoff and thus more pollutants washed into water (Regier et al., 2020), the peak of which in extreme precipitation could be even worse than point source pollution according to Pak et al. (2021). Thus, the pollutant discharge from urban areas could exceed the self-purification capacity of water bodies and deteriorate water quality (Lai et al., 2013). In the dry season, declining water volumes would diminish the dilution towards contaminants and the self-purification capacity of water environment, leading to water quality decline (Xiao et al., 2016; Bussi et al., 2017). Regarding TP, our result showed the dry season could amplify its correlation with urban land than the wet season (Fig. 4), which might result from the concentration of point-source pollutants and the release of particulate phosphorus from sediment when water levels decreasing (Bussi et al., 2017; Record et al., 2016). In addition, our study found that globally, dry and wet seasons amplified TN output from urban area to a similar extent (Fig. 4), answering the divergent in regional studies. Some believed that nitrogen tended to be deposited in surface soils in the dry season with poor hydrological connectivity, reducing N export from urban lands into receiving water (Ferrier et al., 1995; Wu et al., 2022). However, other scholars demonstrated that the dry season could amplify the pollution from urban lands upon TN (Ding et al., 2015; Zhang et al., 2019). Additionally, our result witnessed an increasing effect of urban lands on COD as precipitation rose (Fig. 4), considered to be related to increasing runoff, especially in slightly urbanized catchments without complete drainage systems (Liu et al., 2017; Nafi'Shehab et al., 2021), and as comparison highly-urbanize catchment might observe higher COD in dry seasons (Chen et al., 2016; Liu et al., 2017).

Furthermore, as demonstrated in Fig. 4, arid areas tend to suffer more harsh deterioration in water quality as urban land sprawl worldwide, taking New Mexico in the USA (Regier et al., 2020) and Xinjiang in China (Wang et al., 2022b) as examples. Low quality and quantity of water availability would exacerbate water scarcity in arid regions, exacerbating inequalities in global water scarcity and requiring urgent attention (Wang et al., 2024).

Combined with spreading hotspots on the impacts of urban sprawl on the water environment in recent years (Fig. 1), we found that rapid urbanization in developing regions in arid and tropic areas, especially those without sound drainage and sewage treatment systems and prone to stormwater flooding hazards from concentrated precipitation, could lead to severe pathogens contamination (mainly fecal coliform) and take thousands of lives through infectious disease spread (Ashbolt,2004). Examples include the pollution in the Mun River watershed in Thailand (Yadav,2019), the Mekong tributary watersheds in Lao P.D.R (Ribolzi et al.,2011) and the Intag area in Ecualor (Knee and Encalada, 2014). As a comparison, the water quality had improved through industrial restructuring and water management in some developed regions, taking Lake Ontario in Canada (Croft-White et al., 2017) and North Canal River in China as examples (Zhu et al., 2023). The imbalance in socio-economic development aggravated the inequity in global water security.

4.4. Correlation of forest with water quality

Our meta-analysis concluded that forest cover significantly decreased the risk of water pollution (Fig. 2b), especially the biological and heavy metal contamination, suggesting the importance of forest restoration in global urbanization for water security. Forests could cool water flow and therefore increase the solubility of oxygen in water (Garner et al., 2014), which was necessary for the aquatic organism respiration and the biological and biochemical decomposition of organic matter (Ansa-Asare, 2000). Moreover, given that (i) tree canopy was key to stormwater management and soil erosion regulation, (ii) the interception by tree roots and litters, (iii) the absorption of bioavailable contaminants by robust roots, the forest could cogently prevent the solids and nutrients from transporting into water (Lowrance et al., 1997; Quinn and Stroud, 2002; Harris, 2001).

Latitude ranked top as the contributing factor in changes in the correlation of forest with water quality (Fig. 6). The low-latitude forests were the most efficient at water purification (Figs. 3 and 6). The benefits of forest cover for water quality seemed to gradually decrease as the latitude increases (Fig. 3). The biomass of forest was considered as an underlying contributor in this pattern since observations demonstrated that the highest aboveground biomass of forests occurred in tropical forests and then the northern temperate forests (Schepaschenko et al., 2019). Another potential explanation was that the high temperature and evapotranspiration increased the solubility of bioavailable contaminants in water (such as phosphorus) ((Yang et al., 2023; Cheng et al., 2020) and accelerated chemical and biochemical processes (such as denitrification and carbon released from organic matter decomposition) (Dawson and Murphy, 1972; Aerts, 1997). However, the tropical forests have been suffering from deforestation, particularly in those underdeveloped countries relying the trade (Hoang and Kanemoto, 2021; Zhang and Wei, 2021), which called on global sharing sustainable development and water security responsibility.

Additionally, hinted by outliers in our global analysis, some exceptions need attention in the water purification functions of forests. Firstly, hilly areas and flooded areas seemed to promote the probability of forest TSS, TN and TP output owing to the erosion of topsoils (Quinn and Stroud, 2002; Tram et al., 2022; Tromboni, 2021). Secondly, the negative connection between forest coverage and DO observed in the outliers might be elucidated by two reasons: excess organic matter input from litter, especially in low-flow periods (Abdul-Aziz and Ahmed, 2017); and the static wind and sequent still water status caused by enclosed forest, which was not conducive for oxygen exchange (Scully, 2010; Chen et al., 2021a). Additionally, unfragmented forest patches with complex edge shapes could increase the benefits of water purification, as supported by studies in Brazil (de Mello et al., 2020), Malaysia (Nafi'Shehab et al., 2021), China (Yu et al., 2013), Korea (Lee et al., 2009), and the United States (Carey et al., 2011).

4.5. Connection of wetlands with water quality

Although numerous ecological experiments in small scales proved the role of wetlands in removing pollutants from water, our global meta-analysis showed that changes in wetland coverage in watershed did not have a significant impact on water quality, which might be because the coverage of wetland was rather small in the whole landscape (Fig. 2d). For mechanism, wetlands achieved water purification mainly through physicochemical processes represented by sedimentation and adsorption and biochemical processes represented by wetland plants' uptake and soil microorganisms' degradation (Verhoeven et al., 2006). In anaerobic wetland environments, denitrifying bacteria sequentially converted inorganic nitrogen into nitrogen gas, thus removing nitrogen from the water (Gersberg, 1986; Verhoeven et al., 2006; Morrissy et al., 2021). Apart from being directly absorbed by wetland plants (Vymazal, 2007), phosphorus was easily bound and deposited in the wetland soil through a series of complex reactions with metal ions in the sediments

(Records et al., 2016). The decreasing effects on TN, nitrate and TP could be partly observed in the overall effects of wetlands in Fig. 2d but were very ambiguous (cross the 0 line). The mist came from some references reflecting the wetland coverage positively correlated with nutrient concentration (Rothenberger, 2009; Giri et al., 2018; Bu et al., 2014). We surmised that one reason could be the nitrogen fixation by wetland plants converting airborne nitrogen to reactive nitrogen in water (Jordan, 2011). Additionally, an explanatory phenomenon was that the wetland could absorb or release nutrients in water depending on how much the concentration was and whether it was saturated or not (Day et al., 2004; Verhoeven et al., 2006). Previous studies indicated the existence of critical loads, whereby both community structure and ecological functions, including water purification, would be shifted upon reaching a certain level of nutrient concentrations in wetland aquatic environments (Verhoeven et al., 2006). Hence, intense nitrogen and phosphorus inputs from surrounding urban and agricultural lands exceeding the loads would lead the wetland to behave as a nutrient exporter.

Our meta-analysis revealed COD and DOC in water significantly positively responded to wetland coverage worldwide (Fig. 2d), typically observed in studies in Canada (Chen et al., 2021b), the USA (Tu, 2011), and China (Bu et al., 2014). Owing to the flooded and oxygen-deficient state of the wetland, the proportion of organic carbon decomposition was always limited (Chen, 2023). Coupled with captured incoming biomass and organic matter, wetlands could sequester and store carbon in soil (Yu et al., 2021), performing as a carbon sink (Freeman et al., 2004). Increasing temperature and future warming would enhance the correlation between wetlands and carbon concentration in water by accelerating the organic carbon leaching from soil texture and increasing the organic matter in water (Freeman et al., 2004; Evans et al., 2005).

The correlation of wetland coverage with COD levels in water significantly differed among climatic zones and latitudes (Table 1, Fig. 6). Cold areas and high-latitude regions witnessed a distinctively high effect size (Fig. 4), which was highly coherent with the previous findings in boreal peatlands by Pastor et al. (2003) and the global variation patterns of nitrogen revealed by Jordan (2011). That could result from the long freezing period and long water residence in the cold high-latitude environment. Besides, low temperatures generally restricted microbial activity and chemical reaction rates, reducing organic matter decomposition efficiency (Andersson, 2000), DOC catabolism efficiency, and nitrification and denitrification efficiency etc. (Evans et al., 2005; Morrissy et al., 2021), and thus increased the total concentration of organic carbon in water. Other moderators (seasonality, spatial scale, year, etc.) hardly showed influence on the effects of wetland coverage changes on water quality in our analysis (Table 1, Figs. 4-6), perhaps related to their self-regulating capacity.

4.5. Limitations and future directions

Although this study revealed the global effects of landscape changes on surface water quality based on extensive studies, sample size and distribution still majorly restricted this data-driven meta-analysis. Wetlands did not receive that much attention in the compositive landscape studies compared with other landscape compositions (Fig. 2a~e). The previous studies in the developing countries around the equator and the southern hemisphere were relatively sparse (Fig. 3), calling for more stakeholders caring for the existing and potential water quality issues under the landscape changes in those distribution gaps.

Future research should follow technological and methodological developments. High-frequency *in-situ* water quality monitoring technology such as the Online-monitoring Systems (Ministry of Ecology and Environment, 2019) can effectively improve the temporal continuity in water sampling and the standardization of water quality measurement. Hyperspectral remote sensing technology combined with machine learning algorithms contributes to water quality data with high spatial and temporal resolution at more ambitious research scales at low cost (Ramadas and Samantaray, 2018). As monitoring and prediction models of climate changes and hydroclimatic extremes continue to be refined, future research is expected to integrate the drivers of water quality changes considering changes in climate and landscape patterns and other factors such as hydrological processes and human activities (van Vliet et al., 2023).

5. Conclusions

Taking advantage of meta-analysis and a fusion of various statistical and machine learning methods, our study compiled the global effects of landscape changes on water quality. Results revealed the expansion of urban land was most responsible for the deterioration of water quality, more so than agricultural land even in nutrient pollution. Forest coverage in watersheds generally exerts improvement in water quality. The intuitive water purification function of wetlands is obscured in mixed landscape studies, but wetlands are significantly and positively correlated with organic matter-related indicators. The effects of those landscape changes on water quality are moderated to varying degrees by factors such as latitude, water body type, seasonality, climatic zone, and spatial scale, and gradually increase over time. The impacts of surface land change on water environment quality are such a universal and growing problem that sustainable LULC management and enhanced water protection through nature-based solutions are urgently needed. This paper also revealed the regional unevenness in the studies and appealed to further attention to global water equity and environmental justice under intensified climate changes.

CRediT authorship contribution statement

Xinying Shi: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Dehua Mao:** Writing – review & editing, Visualization, Validation, Funding acquisition, Conceptualization. **Kaishan Song:** Writing – review & editing, Validation. **Hengxing Xiang:** Writing – review & editing. **Sijia Li:** Writing – review & editing. **Zongming Wang:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (U23A2008 and 42171379), the funding from Youth Innovation Promotion Association of CAS (2017277), and the Young Scientist Group Project of Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences (2022QNXZ03).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.watres.2024.121946.

References

Abdul-Aziz, O.I., Ahmed, S., 2017. Relative linkages of stream water quality and environmental health with the land use and hydrologic drivers in the coastal-urban watersheds of southeast Florida. GeoHealth 1 (4), 180–195.
Aerts, R., 1997. Climate, leaf litter chemistry and leaf litter decomposition in terrestrial ecosystems: a triangular relationship. Oikos. 439–449.
Andersson, S., Nilsson, S.I., Saetre, P., 2000. Leaching of dissolved organic carbon (DOC) and dissolved organic nitrogen (DON) in mor humus as affected by temperature and pH. Soil Biol. Biochem. 32 (1), 1–10.
Ansa-Asare, O.D., Marr, I.L., Cresser, M.S., 2000. Evaluation of modelled and measured patterns of dissolved oxygen in a freshwater lake as an indicator of the presence of biodegradable organic pollution. Water. Res. 34 (4), 1079–1088.
Ashbolt, N.J., 2004. Microbial contamination of drinking water and disease outcomes in developing regions. Toxicology. 198 (1-3), 229–238.
Asuero, A.G., Sayago, A., González, A.G., 2006. The Correlation Coefficient: An Overview. Crit. Rev. Anal. Chem. 36 (1), 41–59. https://doi.org/10.1080/10408340500526766.
Beck, H.E., et al., 2018. Present and future Köppen-Geiger climate classification maps at 1-km resolution. Sci. Data 5 (1), 1–12.
Bhattarai, G., Srivastava, P., Marzen, L., Hite, D., Hatch, U., 2008. Assessment of economic and water quality impacts of land use change using a simple bioeconomic model. Environ. Manage 42, 122–131.
Borenstein, M., Hedges, L.V., Higgins, J.P., Rothstein, H.R., 2009. Introduction to meta-analysis. Wiley, Chichester.
Borenstein, M., Hedges, L.V., Higgins, J.P., Rothstein, H.R., 2010. A basic introduction to fixed-effect and random-effects models for meta-analysis. Res. Synth. Methods 1 (2), 97–111.
Brauns, M., Allen, D.C., Boëchat, I.G., Cross, W.F., Ferreira, V., Graeber, D., Gücker, B., 2022. A global synthesis of human impacts on the multifunctionality of streams and rivers. Glob. Chang. Biol. 28 (16), 4783–4793.
Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.
Broussard, W., Turner, R.E., 2009. A century of changing land-use and water-quality relationships in the continental US. Front. Ecol. Environ. 7 (6), 302–307.
Bu, H., Meng, W., Zhang, Y., Wan, J., 2014. Relationships between land use patterns and water quality in the Taizi River basin, China. Ecol. Indic. 41, 187–197.
Bullard, W.E., 1966. Effects of land use on water resources. J. (Water Pollut. Control Federat.) 38 (4), 645–659. http://www.jstor.org/stable/25035540.
Bussi, G., Janes, V., Whitehead, P.G., Dadson, S.J., Holman, I.P., 2017. Dynamic response of land use and river nutrient concentration to long-term climatic changes. Sci. Total Environ. 590, 818–831.
Carey, R.O., Migliaccio, K.W., Li, Y., Schaffer, B., Kiker, G.A., Brown, M.T., 2011. Land use disturbance indicators and water quality variability in the Biscayne Bay Watershed, Florida. Ecol. Indic. 11 (5), 1093–1104.
Carpenter, S.R., Caraco, N.F., Correll, D.L., Howarth, R.W., Sharpley, A.N., Smith, V.H., 1998. Nonpoint pollution of surface waters with phosphorus and nitrogen. Ecol. Appl. 8 (3), 559–568.
Chen, D., Wei, W., Chen, L., 2017. Effects of terracing practices on water erosion control in China: A meta-analysis. Earth. Sci. Rev. 173, 109–121.
Chen, H., Yu, Z., Wu, N., Wang, Y., Liu, X., 2023. C-wetland": a new paradigm to enhance conservation of carbon-rich wetlands. The Innovation 4 (2), 100403.
Chen, Q., Mei, K., Dahlgren, R.A., Wang, T., Gong, J., Zhang, M., 2016. Impacts of land use and population density on seasonal surface water quality using a modified geographically weighted regression. Sci. Total Environ. 572, 450–466.
Chen, T., Cui, D., Yuan, Y., Liu, J., Huang, M., Li, Y., 2021a. Changes in water quality and land use structure in the green-belt area around Shanghai. J. East China Normal Univ. (Natural Science) 2021 (4), 81.
Chen, Z., An, C., Tan, Q., Tian, X., Li, G., Zhou, Y., 2021b. Spatiotemporal analysis of land use pattern and stream water quality in southern Alberta, Canada. J. Contam. Hydrol. 242, 103852.
Cheng, X., Huang, Y., Li, R., Pu, X., Huang, W., Yuan, X., 2020. Impacts of water temperature on phosphorus release of sediments under flowing overlying water. J. Contam. Hydrol. 235, 103717.
Chiang, L.C., Wang, Y.C., Chen, Y.K., Liao, C.J., 2021. Quantification of land use/land cover impacts on stream water quality across Taiwan. J. Clean. Prod. 318, 128443.
Croft-White, M.V., Cvetkovic, M., Rokitnicki-Wojcik, D., Midwood, J.D., Grabas, G.P., 2017. A shoreline divided: twelve-year water quality and land cover trends in Lake Ontario coastal wetlands. J. Great. Lakes. Res. 43 (6), 1005–1015.
Dale, V.H., 1997. The relationship between land-use change and climate change. Ecol. Appl. 7 (3), 753–769.
Dauer, D.M., Ranasinghe, J.A., Weisberg, S.B., 2000. Relationships between benthic community condition, water quality, sediment quality, nutrient loads, and land use patterns in Chesapeake Bay. Estuaries 23 (1), 80–96.
Dawson, R.N., Murphy, K.L., 1972. The temperature dependency of biological denitrification. Water. Res. 6 (1), 71–83.
Day Jr, J.W., Ko, J.Y., Rybczyk, J., Sabins, D., Bean, R., Berthelot, G., Twilley, R, 2004. The use of wetlands in the Mississippi Delta for wastewater assimilation: a review. Ocean Coastal Manag. 47 (11-12), 671–691.
de Mello, K., Taniwaki, R.H., de Paula, F.R., Valente, R.A., Randhir, T.O., Macedo, D.R., Hughes, R.M., 2020. Multiscale land use impacts on water quality: Assessment, planning, and future perspectives in Brazil. J. Environ. Manage 270, 110879.
Deeks, J. J., Higgins, J.P.T., Altman, D.G (eds). (2022). Chapter 10: Analysing data and undertaking meta-analyses. In: Higgins, J.P.T., Thomas, J., Chandler, J., Cumpston, M., Li, T., Page, M.J., Welch, V.A. (eds). *Cochrane Handbook for Systematic Reviews of Interventions* version 6.3 (updated February 2022). Cochrane. Available from www.training.cochrane.org/handbook.
Delpla, I., Rodriguez, M.J., 2014. Effects of future climate and land use scenarios on riverine source water quality. Sci. Total Environ. 493, 1014–1024.
Ding, J., Jiang, Y., Fu, L., Liu, Q., Peng, Q., Kang, M., 2015. Impacts of land use on surface water quality in a subtropical River Basin: a case study of the Dongjiang River Basin, Southeastern China. Water. (Basel) 7 (8), 4427–4445.
Erol, A., Randhir, T.O., 2013. Watershed ecosystem modeling of land-use impacts on water quality. Ecol. Modell. 270, 54–63.
Evans, C.D., Monteith, D.T., Cooper, D.M., 2005. Long-term increases in surface water dissolved organic carbon: observations, possible causes and environmental impacts. Environ. Pollut. 137 (1), 55–71.
Ewane, E.B., 2020. Assessing land use and landscape factors as determinants of water quality trends in Nyong River basin, Cameroon. Environ. Monit. Assess. 192 (8), 507.
Feng, Z., Wang, L., Wan, X., Yang, J., Peng, Q., Liang, T., Rinklebe, J., 2022. Responses of soil greenhouse gas emissions to land use conversion and reversion—a global meta-analysis. Glob. Chang. Biol. 28 (22), 6665–6678.
Ferrier, R.C., Whitehead, P.G., Sefton, C., Edwards, A.C., Pugh, K., 1995. Modelling impacts of land use change and climate change on nitrate-nitrogen in the River Don, North East Scotland. Water. Res. 29 (8), 1950–1956.
Flood, M.T., Hernandez-Suarez, J.S., Nejadhashemi, A.P., Martin, S.L., Hyndman, D., Rose, J.B., 2022. Connecting microbial, nutrient, physiochemical, and land use variables for the evaluation of water quality within mixed use watersheds. Water. Res. 219, 118526.
Fluet-Chouinard, E., Stocker, B.D., Zhang, Z., Malhotra, A., Melton, J.R., Poulter, B., McIntyre, P.B., 2023. Extensive global wetland loss over the past three centuries. Nature 614 (7947), 281–286.
Fox, G.A., Negrete-Yankelevich, S., Sosa, V.J. (Eds.), 2015. Ecological Statistics: Contemporary Theory and Application. Oxford University Press.
Freeman, C., Fenner, N., Ostle, N.J., Kang, H., Dowrick, D.J., Reynolds, B., Hudson, J., 2004. Export of dissolved organic carbon from peatlands under elevated carbon dioxide levels. Nature 430 (6996), 195–198.
Galbraith, L.M., Burns, C.W., 2007. Linking land-use, water body type and water quality in southern New Zealand. Landsc. Ecol. 22, 231–241.
Garner, G., Malcolm, I.A., Sadler, J.P., Hannah, D.M., 2014. What causes cooling water temperature gradients in a forested stream reach? Hydrol. Earth. Syst. Sci. 18 (12), 5361–5376.
Gersberg, R.M., Elkins, B.V., Lyon, S.R., Goldman, C.R., 1986. Role of aquatic plants in wastewater treatment by artificial wetlands. Water. Res. 20 (3), 363–368.
GetData Graph Digitizer, 2013. GetData graph digitizer (2.25). Computer Software.
Giri, S., Qiu, Z., Zhang, Z., 2018. Assessing the impacts of land use on downstream water quality using a hydrologically sensitive area concept. J. Environ. Manage 213, 309–319.
Gorgoglione, A., Gregorio, J., Rios, A., Alonso, J., Chreties, C., Fossati, M., 2020. Influence of land use/land cover on surface-water quality of Santa Lucìa river, Uruguay. Sustainability. 12 (11), 4692.
Gossweiler, B., Wesström, I., Messing, I., Romero, A.M., Joel, A., 2019. Spatial and temporal variations in water quality and land use in a semi-arid catchment in Bolivia. Water. (Basel) 11 (11), 2227.
Gove, N.E., Edwards, R.T., Conquest, L.L., 2001. Effects of scale on land use and water quality relationships: a longitudinal basin-wide perspective. JAWRA J. Am. Water Res. Assoc. 37 (6), 1721–1734.
Grömping, U., 2009. Variable importance assessment in regression: linear regression versus random forest. Am. Stat. 63 (4), 308–319.
Gyimah, R.A.A., Karikari, A.Y., Gyamfi, C., Asantewaa-Tannor, P., Anornu, G.K., 2020. Spatial evaluation of land use variability on water quality of the Densu Basin, Ghana. Water Sci. Technol. 20 (8), 3000.
Haith, D.A., 1976. Land use and water quality in New York rivers. J. Environ. Eng. Division 102 (1), 1–15.
Hakamata, T., Hirata, T., Muraoka, K., 1992. Evaluation of land use and river water quality of the Tsukuba Mountains ecosystem, Japan. Catena (Amst) 19 (5), 427–439.
Harris, G.P., 2001. Biogeochemistry of nitrogen and phosphorus in Australian catchments, rivers and estuaries: effects of land use and flow regulation and comparisons with global patterns. Marine Freshwater Res. 52 (1), 139–149.
Hoang, N.T., Kanemoto, K., 2021. Mapping the deforestation footprint of nations reveals growing threat to tropical forests. Nature Ecol. Evol. 5 (6), 845–853.
Horppila, J., 2019. Sediment nutrients, ecological status and restoration of lakes. Water. Res. 160, 206–208.
International Food Policy Research Institute (IFPRI) and VEOLIA (2015) *The murky future of global water quality: new global study projects rapid deterioration in water quality.* A White Paper. Washington, D.C. and Chicago, IL. Available at: https://www.ifpri.org/publication/murky-future-global-water-quality-new-global-study-projects-rapid-deterioration-water (Assessed: 09 August 2023).
Jordan, S.J., Stoffer, J., Nestlerode, J.A., 2011. Wetlands as sinks for reactive nitrogen at continental and global scales: a meta-analysis. Ecosystems. 14, 144–155.
Jung, K.W., Lee, S.W., Hwang, H.S., Jang, J.H., 2008. The effects of spatial variability of land use on stream water quality in a coastal watershed. Paddy Water Environ. 6, 275–284.
Kang, J.H., Lee, S.W., Cho, K.H., Ki, S.J., Cha, S.M., Kim, J.H., 2010. Linking land-use type and stream water quality using spatial data of fecal indicator bacteria and heavy metals in the Yeongsan river basin. Water. Res. 44 (14), 4143–4157.
Khan, M.N., Mohammad, F., 2014. Eutrophication: challenges and solutions. Eutrophication: Causes, Consequences and Control: Volume 2, pp. 1–15.
Knee, K.L., Encalada, A.C., 2014. Land use and water quality in a rural cloud forest region (Intag, Ecuador). River. Res. Appl. 30 (3), 385–401.
Lai, Y.C., Tu, Y.T., Yang, C.P., Surampalli, R.Y., Kao, C.M., 2013. Development of a water quality modeling system for river pollution index and suspended solid loading evaluation. J. Hydrol. (Amst) 478, 89–101.

Lee, S.W., Hwang, S.J., Lee, S.B., Hwang, H.S., Sung, H.C., 2009. Landscape ecological approach to the relationships of land use patterns in watersheds to water quality characteristics. Landsc. Urban. Plan. 92 (2), 80–89.
Legendre, P., Legendre, L., 2012. *Numerical Ecology* [*electronic resource*], 3rd English ed. Elsevier, Amsterdam; Boston.
Liaw, A., Wiener, M., 2002. Classification and regression by randomForest. R News 2 (3), 18–22.
Liu, J., Niyogi, D., 2019. Meta-analysis of urbanization impact on rainfall modification. Sci. Rep. 9 (1), 7301.
Liu, J., Zhang, X., Wu, B., Pan, G., Xu, J., Wu, S., 2017. Spatial scale and seasonal dependence of land use impacts on riverine water quality in the Huai River basin, China. Environ. Sci. Pollut. Res. 24, 20995–21010.
Lowrance, R., Altier, L.S., Newbold, J.D., Schnabel, R.R., Groffman, P.M., Denver, J.M., Robinson, J.L., 1997. Water quality functions of riparian forest buffers in Chesapeake Bay watersheds. Environ. Manage.
Luo, Z., Shao, Q., Zuo, Q., Cui, Y., 2020. Impact of land use and urbanization on river water quality and ecology in a dam dominated basin. J. Hydrol. (Amst) 584, 124655.
Mansaray, A.S., Aamodt, J., Koroma, B.M., 2018. Water pollution laws in sierra leone—a review with examples from the UK and USA. Natural Res. 9 (11), 361–388.
Mao, D., Luo, L., Wang, Z., Wilson, M.C., Zeng, Y., Wu, B., Wu, J., 2018a. Conversions between natural wetlands and farmland in China: a multiscale geospatial analysis. Sci. Total Environ. 634, 550–560.
Mao, D., Wang, Z., Wu, J., Wu, B., Zeng, Y., Song, K., Luo, L., 2018b. China's wetlands loss to urban expansion. Land Degrad. Develop. 29 (8), 2644–2657.
Mehaffey, M.H., Nash, M.S., Wade, T.G., Ebert, D.W., Jones, K.B., Rager, A., 2005. Linking land cover and water quality in New York City's water supply watersheds. Environ. Monit. Assess. 107, 29–44.
Merghadi, A., et al., 2020. Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. Earth. Sci. Rev. 207, 103225 https://doi.org/10.1016/j.earscirev.2020.103225.
Miller, J.D., Hutchins, M., 2017. The impacts of urbanisation and climate change on urban flooding and urban water quality: a review of the evidence concerning the United Kingdom. J. Hydrol.: Reg. Stud. 12, 345–362.
Ministry of Ecology and Environment (2019) *HJ 355-2019: Technical specification for operation of wastewater on-line monitoring system (CODCr, NH3-N et al.)*. Available at: https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201912/W020191227500068358506.pdf. (Accessed: 21 October 2023).
Morée, A.L., Beusen, A.H.W., Bouwman, A.F., Willems, W.J., 2013. Exploring global nitrogen and phosphorus flows in urban wastes during the twentieth century. Global. Biogeochem. Cycles. 27 (3), 836–846.
Morrissy, J.G., Currell, M.J., Reichman, S.M., Surapaneni, A., Megharaj, M., Crosbie, N. D., Ball, A.S., 2021. Nitrogen contamination and bioremediation in groundwater and the environment: a review. Earth. Sci. Rev. 222, 103816.
Nafi'Shehab, Z., Jamil, N.R., Aris, A.Z., Shafie, N.S., 2021. Spatial variation impact of landscape patterns and land use on water quality across an urbanized watershed in Bentong, Malaysia. Ecol. Indicat. 122, 107254.
Nahm, F.S., 2016. Nonparametric statistical tests for the continuous data: the basic concept and the practical use. Korean J. Anesthesiol. 69 (1), 8–14.
Nakagawa, S., Noble, D.W., Senior, A.M., Lagisz, M., 2017. Meta-evaluation of meta-analysis: ten appraisal questions for biologists. BMC. Biol. 15 (1), 1–14.
Olsson, L., Barbosa, H., Bhadwal, S., Cowie, A., Delusca, K., Flores-Renteria, D., Hermans, K., Jobbagy, E., Kurz, W., Li, D., Sonwa, D.J., Stringer, L., 2019. Land Degradation. In: Climate Change and Land: an IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems. https://doi.org/10.1017/9781009157988.006.
Pak, H.Y., Chuah, C.J., Yong, E.L., Snyder, S.A., 2021. Effects of land use configuration, seasonality and point source on water quality in a tropical watershed: a case study of the Johor River Basin. Sci. Total Environ. 780, 146661.
Pastor, J., Solin, J., Bridgham, S.D., Updegraff, K., Harth, C., Weishampel, P., Dewey, B., 2003. Global warming and the export of dissolved organic carbon from boreal peatlands. Oikos. 100 (2), 380–386.
Peiffer, S., Kappler, A., Haderlein, S.B., Schmidt, C., Byrne, J.M., Kleindienst, S., Planer-Friedrich, B., 2021. A biogeochemical–hydrological framework for the role of redox-active compounds in aquatic systems. Nat. Geosci. 14 (5), 264–272.
Pielke Sr, R.A, 2005. Land use and climate change. Science (1979) 310 (5754), 1625–1626.
Qiu, M., Wei, X., Hou, Y., Spencer, S.A., Hui, J., 2023. Forest cover, landscape patterns, and water quality: a meta-analysis. Landsc. Ecol. 38 (4), 877–901.
Quinn, J.M., Stroud, M.J., 2002. Water quality and sediment and nutrient export from New Zealand hill-land catchments of contrasting land use. New Zealand J. Marine Freshwater Res. 36 (2), 409–429.
Ramadas, M., Samantaray, A.K., 2018. Applications of remote sensing and GIS in water quality monitoring and remediation: a state-of-the-art review. Water Remed. 225-246.
Radwan, T.M., Blackburn, G.A., Whyatt, J.D., Atkinson, P.M., 2021. Global land cover trajectories and transitions. Sci. Rep. 11 (1), 12814.
Records, R.M., Wohl, E., Arabi, M., 2016. Phosphorus in the river corridor. Earth. Sci. Rev. 158, 65–88.
Regier, P.J., González-Pinzón, R., Van Horn, D.J., Reale, J.K., Nichols, J., Khandewal, A., 2020. Water quality impacts of urban and non-urban arid-land runoff on the Rio Grande. Sci. Total Environ. 729, 138443.
Ren, W., Zhong, Y., Meligrana, J., Anderson, B., Watt, W.E., Chen, J., Leung, H.L., 2003. Urbanization, land use, and water quality in Shanghai: 1947–1996. Environ. Int. 29 (5), 649–659.
Ribolzi, O., Cuny, J., Sengsoulichanh, P., Mousquès, C., Soulileuth, B., Pierret, A., Sengtaheuanghoung, O., 2011. Land use and water quality along a Mekong tributary in Northern Lao PDR. Environ. Manage 47, 291–302.
Rimba, A.B., Mohan, G., Chapagain, S.K., Arumansawang, A., Payus, C., Fukushi, K., Avtar, R., 2021. Impact of population growth and land use and land cover (LULC) changes on water quality in tourism-dependent economies using a geographically weighted regression approach. Environ. Sci. Pollut. Res. 28, 25920–25938.
Rothenberger, M.B., Burkholder, J.M., Brownie, C., 2009. Long-term effects of changing land use practices on surface water quality in a coastal river and lagoonal estuary. Environ. Manage 44, 505–523.
Rupinski, M.T., Dunlap, W.P., 1996. Approximating Pearson Product-Moment Correlations from Kendall's Tau and Spearman's Rho. Educ. Psychol. Meas. 56 (3), 419–429. https://doi.org/10.1177/0013164496056003004.
Schepaschenko, D., Chave, J., Phillips, O.L., Lewis, S.L., Davies, S.J., Réjou-Méchain, M., Zo-Bi, I.C., 2019. The Forest Observation System, building a global reference dataset for remote sensing of forest biomass. Sci. Data 6 (1), 198.
Schwarzer, G., 2007. Meta: an R package for meta-analysis. R News 7 (3), 40–45.
Scully, M.E., 2010. Wind modulation of dissolved oxygen in Chesapeake Bay. Estuaries Coasts 33, 1164–1175.
Simpson, I.M., Winston, R.J., Brooker, M.R., 2022. Effects of land use, climate, and imperviousness on urban stormwater quality: a meta-analysis. Sci. Total Environ. 809, 152206.
Sliva, L., Williams, D.D., 2001. Buffer zone versus whole catchment approaches to studying land use impact on river water quality. Water. Res. 35 (14), 3462–3472.
Song, X.P., Hansen, M.C., Stehman, S.V., Potapov, P.V., Tyukavina, A., Vermote, E.F., Townshend, J.R., 2018. Global land change from 1982 to 2016. Nature 560 (7720), 639–643.
Sun, L., Chen, J., Li, Q., Huang, D., 2020. Dramatic uneven urbanization of large cities throughout the world in recent decades. Nat. Commun. 11 (1), 5366.
Sweeney, B.W., Bott, T.L., Jackson, J.K., Kaplan, L.A., Newbold, J.D., Standley, L.J., Horwitz, R.J., 2004. Riparian deforestation, stream narrowing, and loss of stream ecosystem services. Proc. Nat. Acad. Sci. 101 (39), 14132–14137.
Tan, L., Ge, Z., Ji, Y., Lai, D.Y., Temmerman, S., Li, S., Tang, J., 2022. Land use and land cover changes in coastal and inland wetlands cause soil carbon and nitrogen loss. Global Ecol. Biogeogr. 31 (12), 2541–2563.
Tong, Y., Wang, M., Peñuelas, J., Liu, X., Paerl, H.W., Elser, J.J., Lin, Y., 2020. Improvement in municipal wastewater treatment alters lake nitrogen to phosphorus ratios in populated regions. Proc. Nat. Acad. Sci. 117 (21), 11566–11572.
Tram, V.N.Q., Somura, H., Moroizumi, T., Maeda, M., 2022. Effects of local land-use policies and anthropogenic activities on water quality in the upstream Sesan River Basin, Vietnam. J. Hydrol.: Reg. Stud. 44, 101225.
Tran, C.P., Bode, R.W., Smith, A.J., Kleppel, G.S., 2010. Land-use proximity as a basis for assessing stream water quality in New York State (USA). Ecol. Indic. 10 (3), 727–733.
Tromboni, F., Dilts, T.E., Null, S.E., Lohani, S., Ngor, P.B., Soum, S., Chandra, S., 2021. Changing land use and population density are degrading water quality in the Lower Mekong Basin. Water. (Basel) 13 (14), 1948.
Tu, J., 2009. Combined impact of climate and land use changes on streamflow and water quality in eastern Massachusetts, USA. J. Hydrol. (Amst) 379 (3-4), 268–283.
Tu, J., 2011. Spatial and temporal relationships between water quality and land use in northern Georgia, USA. J. Integr. Environ. Sci. 8 (3), 151–170.
Tu, J., Xia, Z.G., 2008. Examining spatially varying relationships between land use and water quality using geographically weighted regression I: model design and evaluation. Sci. Total Environ. 407 (1), 358–378.
USGS (2019). *How much water is there on Earth?*. Available at:https://www.usgs.gov/special-topics/water-science-school/science/how-much-water-there-earth (Assessed: 09 August 2023).
Vaighan, A.A., Talebbeydokhti, N., Bavani, A.M., 2017. Assessing the impacts of climate and land use change on streamflow, water quality and suspended sediment in the Kor River Basin, Southwest of Iran. Environ. Earth. Sci. 76, 1–18.
van Vliet, M.T., Thorslund, J., Strokal, M., Hofstra, N., Flörke, M., Ehalt Macedo, H., Mosley, L.M., 2023. Global river water quality under climate change and hydroclimatic extremes. Nature Rev. Earth Environ. 1–16.
Verhoeven, J.T., Arheimer, B., Yin, C., Hefting, M.M., 2006. Regional and global concerns over wetlands and water quality. Trends Ecol. Evol. 21 (2), 96–103.
Viau, E.J., Goodwin, K.D., Yamahara, K.M., Layton, B.A., Sassoubre, L.M., Burns, S.L., Boehm, A.B., 2011. Bacterial pathogens in Hawaiian coastal streams—associations with fecal indicators, land cover, and water quality. Water. Res. 45 (11), 3279–3290.
Vörösmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Davies, P.M., 2010. Global threats to human water security and river biodiversity. Nature 467 (7315), 555–561.
Vymazal, J., 2007. Removal of nutrients in various types of constructed wetlands. Sci. Total Environ. 380 (1-3), 48–65.
Wang, M., Bodirsky, B.L., Rijneveld, R., Beier, F., Bak, M.P., Batool, M., Strokal, M., 2024. A triple increase in global river basins with water scarcity due to future pollution. Nat. Commun. 15 (1), 880.
Wang, M., Janssen, A.B., Bazin, J., Strokal, M., Ma, L., Kroeze, C., 2022a. Accounting for interactions between sustainable development goals is essential for water pollution control in China. Nat. Commun. 13 (1), 730.
Wang, W., Liu, C., Zhang, F., Tan, M.L., Shi, J., Zhang, Z., Xin, H., 2022b. Evaluation of impacts of environmental factors and land use on seasonal surface water quality in arid and humid regions using structural equation models. Ecol. Indic. 144, 109546.
Wei, W., Gao, Y., Huang, J., Gao, J., 2020. Exploring the effect of basin land degradation on lake and reservoir water quality in China. J. Clean. Prod. 268, 122249.
Wilkin, D.C., Jackson, R.W., 1984. Nonpoint water quality contributions from land use. J. Environ. Syst. 13 (2), 127–136.

Winkler, K., Fuchs, R., Rounsevell, M., Herold, M., 2021. Global land use changes are four times greater than previously estimated. Nat. Commun. 12 (1), 2501.

Winton, R.S., Teodoru, C.R., Calamita, E., Kleinschroth, F., Banda, K., Nyambe, I., Wehrli, B., 2021. Anthropogenic influences on Zambian water quality: hydropower and land-use change. Environ. Sci.: Process. Impacts 23 (7), 981–994.

Woldeab, B., Ambelu, A., Mereta, S.T., Beyene, A., 2019. Effect of watershed land use on tributaries' water quality in the east African Highland. Environ. Monit. Assess. 191, 1–13.

Woli, K.P., Nagumo, T., Kuramochi, K., Hatano, R., 2004. Evaluating river water quality through land use analysis and N budget approaches in livestock farming areas. Sci. Total Environ. 329 (1-3), 61–74.

Wu, Q., Yue, K., Ma, Y., Heděnec, P., Cai, Y., Chen, J., Li, Y., 2022. Contrasting effects of altered precipitation regimes on soil nitrogen cycling at the global scale. Glob. Chang. Biol. 28 (22), 6679–6695.

Xiao, R., Wang, G., Zhang, Q., Zhang, Z., 2016. Multi-scale analysis of relationship between landscape pattern and urban river water quality in different seasons. Sci. Rep. 6 (1), 25250.

Xu, M., Zhang, T., Wang, D., Zhao, Y., Xie, Y., Ma, L., 2019. Review and prospect of water pollution prevention and control of China in the forty years of reform and opening-up. Chin. J. Environ. Manag 11, 65–71.

Xu, Q., Yan, T., Wang, C., Hua, L., Zhai, L., 2023. Managing landscape patterns at the riparian zone and sub-basin scale is equally important for water quality protection. Water. Res. 229, 119280.

Yadav, S., Babel, M.S., Shrestha, S., Deb, P., 2019. Land use impact on the water quality of large tropical river: Mun River Basin, Thailand. Environ. Monit. Assess. 191, 1–22.

Yang, Y., Roderick, M.L., Guo, H., Miralles, D.G., Zhang, L., Fatichi, S., Yang, D., 2023. Evapotranspiration on a greening Earth. Nat. Rev. Earth Environ. https://doi.org/10.1038/s43017-023-00464-3.

Yu, C., Xie, S., Song, Z., Xia, S., Åström, M.E., 2021. Biogeochemical cycling of iron (hydr-) oxides and its impact on organic carbon turnover in coastal wetlands: A global synthesis and perspective. Earth. Sci. Rev. 218, 103658.

Yu, D., Shi, P., Liu, Y., Xun, B., 2013. Detecting land use-water quality relationships from the viewpoint of ecological restoration in an urban area. Ecol. Eng. 53, 205–216.

Zalles, V., Hansen, M.C., Potapov, P.V., Parker, D., Stehman, S.V., Pickens, A.H., Kommareddy, I., 2021. Rapid expansion of human impact on natural land in South America since 1985. Sci. Adv. 7 (14), eabg1620.

Zhang, D.W., Li, Y.F., Sun, X., Zhang, F.S., Zhu, H.X., Liu, Y., Zhu, X.D., 2010. Relationship between landscape pattern and river water quality in Wujingang region, Taihu Lake watershed. Environ. Sci. 31 (8), 1775–1783.

Zhang, F., Chen, Y., Wang, W., Jim, C.Y., Zhang, Z., Tan, M.L., Rahman, H.A., 2022. Impact of land-use/land-cover and landscape pattern on seasonal in-stream water quality in small watersheds. J. Clean. Prod. 357, 131907.

Zhang, J., Li, S., Dong, R., Jiang, C., Ni, M., 2019. Influences of land use metrics at multi-spatial scales on seasonal water quality: a case study of river systems in the Three Gorges Reservoir Area, China. J. Clean. Prod. 206, 76–85.

Zhang, M., Wei, X., 2021. Deforestation, forestation, and water supply. Science (1979) 371 (6533), 990–991.

Zhao, J., Lin, L., Yang, K., Liu, Q., Qian, G., 2015. Influences of land use on water quality in a reticular river network area: A case study in Shanghai, China. Landsc. Urban. Plan. 137, 20–29.

Zhu, L., Chen, Y., Wang, Y., Wei, Y., Zheng, H., Zhang, Y., 2023. A comprehensive analysis of impacts of socio-economic development and land use on river water quality in a megacity-region: a case study. Environ. Res. Commun. 5 (2), 025006.

Zou, K.H., Tuncali, K., Silverman, S.G., 2003. Correlation and simple linear regression. Radiology. 227 (3), 617–628.